Exploring the Impact of Frequency Cuts on Gravitational-Wave Parameter Estimation

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Gravitational-wave science has empowered a new era in astrophysical exploration, with the characterization of gravitational-wave signals holding crucial importance. However, accurately characterizing these signals poses challenges, especially in the presence of short-duration noise transients, known as "glitches." A specific strategy employed to address this issue and mitigate the effects of glitches involves cutting a particular frequency range off the signal. In this study, we aim to delve into the critical role that frequency cuts play in gravitational-wave analysis. Through systematic analysis and simulation-based experiments, incorporating data injections and utilizing a neural posterior estimator, we will investigate the effects of different frequency cut configurations on our interpretations of parameter posterior distributions across a diverse array of characteristic waves.

I. INTRODUCTION

Gravitational waves originate predominantly from the accelerated motion of massive objects, such as the orbital movement of black holes and neutron stars. This motion disturbs the fabric of space-time, leading to the propagation of waves in all directions from the source. Traveling at the speed of light, these cosmic ripples convey valuable information about their source's characteristics and provide insights into the fundamental nature of gravity. As gravitational waves travel through space, they induce tiny expansions and contractions in the spatial dimensions they traverse. The measurements of this strain are made possible by the Laser Interferometer Gravitational-Wave Observatory (LIGO) and the Virgo Collaboration (LVC). The LVC operates three detectors: two LIGO detectors located in the United States and one Virgo detector in Italy. The detectors are specialized versions of a Michelson interferometer, which simply consists of two equally long, perpendicular arms with mirrors at their ends. A laser beam is split and sent down each arm, reflecting off the mirrors and then recombining at a central detector. When a gravitational wave passes through, it causes the lengths of the arms to change slightly. This alters the interference pattern when the laser beams recombine, allowing scientists to detect the gravitational waves in the form of weak signals.

One of the major sources of gravitational waves are binary black hole mergers and neutron star mergers, which fall under the category of compact binary coalescences (CBC).The characterization of these waves is especially crucial since they carry promising information about the nature of compact objects. When a signal is detected, the source characterization is made possible by employing Bayesian inference, which relies on having established models for both the signals and the detector noise. In the context of gravitational waves, these signal models are represented by waveform predictions h(θ), which are contingent upon various source parameters θ, such as masses and locations of the objects. Meanwhile, the detector noise is typically assumed to be stationary and Gaussian, characterized by a certain spectrum that can be empirically estimated. Collectively, these models yield the likelihood $p(d|\theta)$ for the observed strain data d, presumed to comprise both signal and noise components. By selecting a prior $p(\theta)$ over the parameters, the posterior distribution is determined through Bayes' theorem as:

$$p(\theta|d) = \frac{p(d|\theta)p(\theta)}{p(d)}, \tag{1}$$

where $p(d)$ acts as a normalizing factor termed the evidence. This posterior distribution encapsulates our beliefs regarding the source parameters, given the observed data.[1]

In order to accomplish the inference, we have chosen to utilize the DINGO method [1] over other conventional methods commonly used in LVC, such as LALInference [2] and Bilby [3]. The primary reason for this choice is the imperative need for speed in conducting numerous trials of parameter estimations. Traditional methods such as LALInference and Bilby employ stochastic algorithms like Markov chain Monte Carlo (MCMC) to characterize the posterior distribution by drawing samples from it. However, these algorithms are computationally intensive, demanding numerous likelihood evaluations for each independent posterior sample. Each likelihood evaluation necessitates a waveform simulation, making the entire inference process time-consuming. However, DINGO is a neural posterior estimation (NDE) model, and has shown to achieve both significantly reduced analysis time and high accuracy. As a likelihood-free and simulation-based inference model, the simple principle of DINGO is to generate numerous simulated datasets, each with its corresponding parameters, and utilize these datasets to train a specific type of neural network called a normalizing flow, which is employed to approximate the posterior distribution. Once the network is trained, it can rapidly produce new posterior samples following a detection.[1]

Accurate source characterization depends on the specific assumptions about the behavior of the detector noise, however, these assumptions are violated when there are short-duration noise transients, called "glitches" present in the signal [4]. Glitches can arise from various reasons such as instrumental artifacts or environmental disturbances, however, their sources are not typically directly identifiable, therefore it is not uncommon for glitches to occur unpredictably in the signal. Throughout their third observing run (O3) [5, 6], the median rate of glitches in the LIGO and Virgo detectors has been reported to have surpassed 1 per minute for the majority of the duration, which indicates that the coincidence of the glitches with gravitational-wave signals are expected quite commonly [7]. Since these glitches corrupt the signal and invalidate the noise assumptions for typical gravitational-wave source characterization processes, their identification and mitigation are crucial for accurate analysis.

The process of identifying and subtracting glitches is not straightforward, leading to the adoption of various strategies. One of the most common and sophisticated methods is the BayesWave algorithm [8], which models the glitch and subtracts it by only using the strain data. The algorithm assumes that the strain data consists of Gaussian noise, a gravitational-wave signal, and a glitch. It models the glitch as a sum of sine-Gaussian wavelets, and these wavelets are marginalized over the parameters using a trans-dimensional Markov chain Monte Carlo (MCMC). As the result of the algorithm, a posterior distribution of time series of the glitch is obtained, and the mitigation is conducted by randomly selecting a sample from the posterior, and subtracting it from the data [7]. Despite the common use of the BayesWave algorithm, various studies, including [9] and [5], have demonstrated that the method may potentially leave residual artifacts within the signal, which is not unexpected since the probability of a randomly drawn sample wavelet accurately capturing the precise characteristics of the glitch is low.

Another approach for glitch mitigation is gwsubstract algorithm [10], which uses information from auxiliary channels. The algorithm assumes that the measured strain is a linear combination of time series from different sources, where one of these sources can be modeled as the convolution of a witness time series and an unknown transfer function. In this approach, the transfer function between the auxiliary sensor and the strain data channel is determined and used to estimate the contribution of the noise source to the strain data. However, the accuracy of this subtraction method depends on the accuracy of the auxiliary sensor and the transfer function estimate [7, 9]. The mentioned systematic and statistical uncertainties of these two methods poses the risk that even after BayesWave or subtract algorithm is used, the data can still be undersubstracted, as shown in [5, 9].

Although the glitches are commonly dealt with by eliminating data in the time domain, it is possible to come across cases where the glitch only affects a specific frequency range. In such instances, addressing data quality issues might involve employing a narrower frequency range during the analysis [11]. This strategy has been adopted in the cases of [5, 9]. In [5], it has been reported that after the application of these methods, the identified glitch is considered unmitigated if the data surrounding the event are inconsistent with Gaussian noise. In such cases, they evaluated the SNR lost by restricting the frequency range of data considered in parameter inference to fully remove the glitch. If the SNR loss is below 10%, they used the reduced frequency range in the analyses. Otherwise, they have used the nominal frequency range. Similarly in [9], to further investigate the relation between the potentially under-substractive glitch mitigation strategies and the estimated spin-precession posteriors, they have limited the frequency range above a progressively increasing lower limit, and evaluated the SNR values as well as posteriors of various parameters for each lower limit. The results showed that even though SNR loss was small, the posterior for the spin-precession parameter χ_{p} became less informative when a more increased lower limit was used, possibly indicating that the glitch remnants were causing a misleading estimation of the posterior.

While previous studies, including [9] and [5], have explored the benefits of constraining the frequency range of data primarily for mitigating the remnants of glitches, our investigation suggests that frequency cuts may have overlooked implications. An example of this concern can be found in [7]. In this study, all three methods described have been employed and compared by their SNR values and posterior distributions. As shown in the Figure 1, when the lower frequency limit was raised, the posteriors for spin parameters became less informative, and more influenced by the prior. Expectedly, the SNR loss was significant when higher limits were placed on the lower frequency. The results concluded that the glitch subtraction strategies narrowed the posterior distributions, and only caused a little change in SNR, therefore indicating their superiority over frequency cuts. However, of particular interest is the unexpected revelation that different frequency cut configurations led to distinctly different estimations for the same parameter, implying a complex scenario. As shown in Figure 1, the figure demonstrated a significant differentiation in the posteriors for the χ_{eff} parameter, with noticeable shifts across the plot, when different frequency range limits were applied. This demonstration implies a sophisticated relation between frequency cuts and source characterization for gravitational-wave signals.

II. OBJECTIVE

The goal of this research is to investigate the intricate relationship between frequency cuts and the estimation

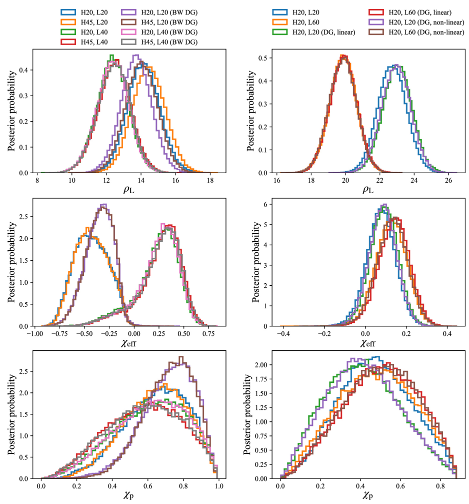

FIG. 1. Graphs illustrating the posterior distributions of matched-filter signal-to-noise ratio (SNR) in the LIGO Livingston detector ρL (Top), effective spin parameter $\chi_{\rm eff}$ (Middle), and effective precession parameter $\chi_{\rm p}$ (Bottom) across various mitigation approaches for two seperate cases, GW191109 (Left) and GW200129 (Right). Reproduced from [7].

of source characteristics in gravitational-wave data analysis. Our study will employ a systematic approach involving data injection, network training, and posterior analysis. Our methodology includes generating simulated signal+noise datasets, implementing various frequency cut configurations, and training neural networks to obtain posterior distributions of source parameters for simulated gravitational-waveforms. By analyzing the resulting posterior distributions, we seek to understand how different frequency cut limits affect the estimation of each source parameter separately.

This analysis will shed light on how different parameters react to frequency cuts, and also enable us to interpret these results across a wide range of waveform characteristics. Ultimately, we plan to establish a definitive understanding of the relationship between source characteristics and frequency ranges. We anticipate that this research will deepen our insight into the intricate nature of gravitational-wave signals, and we aim to pave the way for more informed and refined approaches to signal cleaning, mitigation processes, and gravitational wave analysis techniques in future studies.

III. APPROACH

To achieve our research objectives, we will first simulate gravitational-wave waveforms using the IMRPhenomPv2 model [12] and inject them into Gaussian noise. While glitches are not initially included in our plan, we may also consider incorporating them into the generated data to conduct further investigations, although this aspect is not yet confirmed. Similarly, given that the choice of waveform models plays a significant role in the parameter estimation process due to their respective strengths and limitations, we might also consider exploring alternative waveform models and assessing their impact on the results. The simulated data will be designed to encompass various source characteristics. By generating a range of waveform configurations, we will be able to explore how different signal properties interact with frequency cuts.

Next, we will implement various ranges of frequency cuts to mimic different signal processing scenarios. Each set of frequency cuts will correspond to a distinct training setup for the DINGO network. Therefore, we will train multiple DINGO networks with different frequency cut configurations.

Once the networks are trained, we will feed them with the injected data to obtain posterior distributions for the signal parameters. These posterior distributions will be analyzed, and following the acquisition of the posterior distributions, we will derive various statistics and conduct comprehensive analyses to examine and gain insights into the relationship between frequency cuts and parameter estimation.

IV. TIMELINE

This program will span a duration of 10 weeks, structured mainly into two separate phases. The initial weeks will primarily focus on preparatory activities and training, while the following weeks will center on implementation and rigorous testing. The tentative objectives outlined for this schedule are as follows:

A. Training Phase

- Acquiring proficiency in working with computer systems and relevant tools
- Familiarizing oneself with pertinent literature and research in the field
- Studying the syntax of DINGO and mastering coding procedures necessary for network training and achieving desired outcomes
- Conducting training for neural networks
- Strategizing analysis plans and delineating specifics for targeted focus
- Preparing data injections for experimentation
- Concurrently, conducting tests to compare various aspects of the DINGO model with the alternative models

B. Implementation Phase

- Implementing various frequency cut configurations on injected data
- Testing the neural network with injected data to derive posterior distributions
- Analyzing resultant data and generating requisite statistics for comprehensive interpretation
- Preparing for final reporting and presentations, which involves summarizing findings

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